

# Interactions between consumers and firms

## Identifying the Direct Mail-prone Consumer

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**SOM-theme F Interactions between consumers and firms**

### Abstract

Current modeling research in target marketing usually stresses the identification of profitable names for specific mailings. There is little recent research about the characteristics of typical direct mail (DM) customers. In this paper we determine the link between customers' socio-demographic characteristics and their propensity of purchasing products through the mail. To that end, we hypothesize the existence of a latent characteristic DM-proneness, which represents a consumer's tendency to shop via direct mail. Our model links the socio-demographics of customers to their self-reported purchase behavior through the latent DM-proneness construct in a MIMIC model. We also introduce a second latent construct, DM-information interest, which represents the desire to receive direct offers through the mail. The MIMIC model allows for testing the influence of DM-information interest on DM-proneness. The model is fit on actual consumer data using the LISREL program. The program findings show that the characteristics of the DM-prone and the DM information interested are similar, and that DM-information interest appears to directly affect DM-proneness.

Keywords: Direct marketing, Consumer proneness, Structural equation modeling

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## 1. INTRODUCTION

Modeling in target marketing usually refers to the identification of profitable names for specific mailings. Indeed, every direct marketing statistician makes an imaginary picture of the typical buyer from each product test he or she analyzes. But how clear is our understanding of the customers who receive each direct mail offer with zeal, practically regardless of what is being sold? Very little research has been published recently about the characteristics of customers open to purchasing through a direct channel. On the contrary, more research has been performed trying to identify the customers who wish to receive no solicitations at all. This paper attempts to increase our understanding of the socio-demographic background of the typical direct mail (DM) consumer by identifying the characteristics of people who are prone to make purchases through the mail.

In the marketing literature one repeatedly finds studies of various shopping-related preferences referred to as ‘pronenesses.’ Proneness is defined briefly as the tendency to do something. Direct Mail-proneness is, to our knowledge, a new concept. We hypothesize the existence of an innate proneness regarding mail order purchasing. DM-proneness is thus the tendency to shop through the mail.

Knowing who the DM-prone are can be advantageous in several regards. Offer designers can tailor direct mail offers more specifically to the DM-prone, or they can create new offers to appeal to the segment generally uninterested in DM. Selection criteria can be set based on the characteristics of DM-prone. Given that a direct marketer has information on the socio-demographics of prospect customers for his/her firm, knowledge of the socio-demographics of the DM-prone in general can help in highlighting which segments of the population should be targeted for customer base growth.

DM-proneness cannot be measured directly, and is a latent construct. We employ the Multiple indicators and multiple causes (MIMIC) model as developed by Jöreskog and Goldberger (1975) in order to derive the link between a customer’s socio-demographics and their likelihood of making DM purchases, through this construct.

Further, we introduce a second latent construct, DM-information interest, which is the extent to which a consumer desires in-home delivery of catalogs and brochures. We hypothesize that DM-information interest is a factor causing DM-proneness. We test this hypothesis with the aid of a MIMIC model. In addition, the MIMIC model allows us to analyze the socio-demographics that influence both DM-proneness and DM-information interest. One can thus compare the socio-demographics of those with DM-information interest and the DM-prone.

The concept of tailoring offers to consumers is elaborated in Hoekstra, Leeflang and Wittink (1999). Their “Customer Concept” includes individualized

communications from firms selling goods and services. The DM-prone and DM-information interested should be approached with offers appealing to their needs and styles of fulfilling them.

This article is organized as follows. In Section 2 a review of prior related research is given. In Section 3 we develop the framework for studying the causes and indicators of DM-proneness. We introduce the data we employ to model DM-proneness and a brief formulation of the MIMIC model is given in Section 4. Within that section we introduce a method to correct for the non-normality of the observed variables. The numerical specification of the research is presented, as are the resulting coefficients and criteria of fit in Section 5. Section 6 concludes with key managerial and research implications.

## **2. PRIOR RESEARCH**

Our prior research section recognizes two streams of research related to DM-proneness. We first review home-shopping research, followed by consumer proneness research.

### ***In-home shopping research***

Gillett (1976) reports that in-home shoppers with few exceptions have higher than average socio-economic status, which equates to higher income, social level, education, and occupation of the head of household. Darian (1987) found that “housewives and part-time female workers with children, single males less than 40 years old, households where the female head is aged 40-49 years, and households in the middle income groups” were the most likely to be in-home shoppers. Peterson, Albaum, and Ridgway (1989) examine the characteristics of consumers purchasing directly from salespeople or at sales ‘parties’ either at their own homes, some one else’s home, or at work. This type of sales is termed ‘direct sales.’ Peterson, Albaum, and Ridgway find that purchasers from direct sales companies tend to be younger, more educated, and have higher incomes than those not making purchases from direct sales companies. A recent study of internet shoppers (Donthu and Garcia, 1999) shows that they are generally older and more affluent than those not shopping via internet. Both Darian (1987) and Gillett (1976) caution that the results of studies of the socio-demographic characteristics of in-home shoppers can be misleading due to the narrow range of products likely to be bought from home. In this study we generalize by utilizing a broad variety of product categories sold via mail solicitations and we update the research by using very recent data.

### ***Consumer proneness research***

The predominant consumer proneness characteristic studied is deal-proneness and was introduced by Webster (1965). Deal-proneness entails one’s sensitivity to deals

as a reason for changing purchase patterns. Coupon-proneness, a specific type of deal-proneness, has gained the most attention of shopping-related proneness characteristics with many studies; two are Bawa and Shoemaker (1987) and Bawa, Srinivasan and Srivastava (1997). Although our DM-proneness characteristic is measured differently than most deal-proneness measures, it represents behavior itself, not change in behavior, the methods used to study deal-proneness are relevant to our research. Specifically, we examined studies of deal-proneness as it relates to customer's characteristics. Blattberg and Neslin (1990) summarize the deal-proneness studies published between 1965 and 1989. Most make use of socio-demographics as explanatory variables, a few include behavioral variables, psychographics, and price and media sensitivity. The socio-demographic variables shown to significantly affect deal-proneness are: age, household size, income, female working status, female head of household status, presence of children, sex and education.

Although deal and coupon-proneness make up the majority of consumer proneness research, many other types of proneness have been studied. Loyalty-proneness was hypothesized by Cunningham (1956) and refers to a customer's tendency to remain loyal to a certain brand. Loyalty-proneness over product classes was later shown to be non-significant by Massy, Frank and Lodahl (1968). Richardson, Jain and Dick (1996) suggested a framework for store brand-proneness.

Our study draws on past research in that it seeks to explain attitude toward direct mail purchase based on socio-demographics. One of our contributions is to add a DM-related proneness measure to the growing list of consumer pronenesses represented in the literature, and to increase our understanding of consumer attitudes about direct mail purchasing.

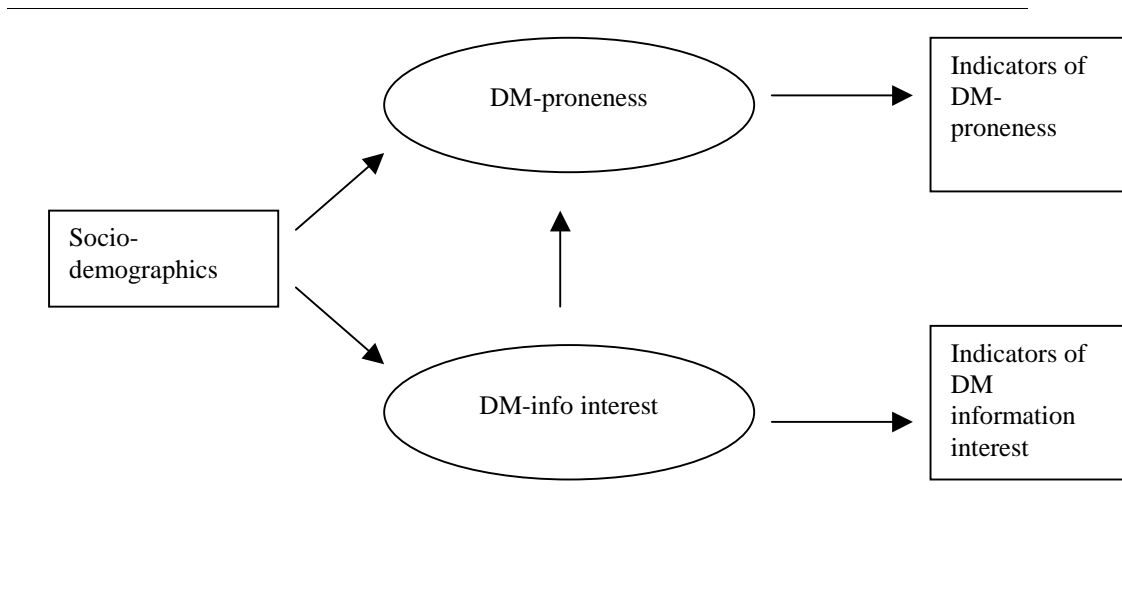
### **3. DM-PRONENESS AND DM-INFORMATION INTEREST FRAMEWORK**

We develop here our own theory regarding DM-proneness and DM-information interest. We postulate that socio-demographics (among other personal characteristics) influence one's attitudes toward purchasing through the mail. See Ajzen and Fishbein (1980), who theorize that socio-demographics affect attitudes about behaviors. Further, we question whether interest in receiving catalogs and brochures, which is a precursor to making a purchase through the mail, actually is a force causing such a purchase. It is possible that the causation here is reversible, i.e., that DM purchase is influencing one's desire for catalogs and brochures. For example, a past positive experience with a DM purchase might make one more receptive to future solicitations. We assume however that since one must receive a solicitation before a purchase can be made, the desire for DM information in part

leads to the purchase. In addition, we hypothesize that socio-demographics affect the interest one has in receiving direct solicitations at home.

Thus interpreted, our framework can be translated into a more concrete model essentially represented by the path diagram in Figure 1. Following the conventions of such diagrams, observables are put in boxes and unobservables in circles. Arrows indicate direct causation.

**FIGURE 1**  
**A Framework for Studying Causes and Indicators of DM-proneness**



Let us thus theorize that socio-demographics affect one's attitude or proneness toward purchasing via direct mail. In order to make a purchase via a direct channel, one must be receptive to direct advertising. Thus, we hypothesize that in addition to socio-demographics, also DM-information interest is a cause of DM-proneness. Proneness to purchase through the mail can be represented by a customer's buying record at various DM outlets. A measure of information interest in the DM sense could be for example a combination of variables indicating request for information in several genres of products which are often offered through direct channels. Our theory is thus broadened by the inclusion of DM-information interest which should influence one's likelihood of purchasing through the mail.

We see in Figure 1 how the hypothesized model is constructed. Socio-demographics influence both DM-proneness and DM-information interest. DM-information interest causes DM-proneness. DM-proneness and DM-information interest are indicated by observed variables relating to the two latent characteristics.

The latent characteristic DM-proneness is the central component of our research. It is this construct we will use to answer the following research questions:

1. Which socio-demographic characteristics indicate a propensity to be DM-prone?
2. Does DM- information interest significantly affect one's level of DM-proneness?
3. Which socio-demographic characteristics indicate the level of DM-information interest and how do these compare with 1?
4. What is the distribution of DM-proneness?

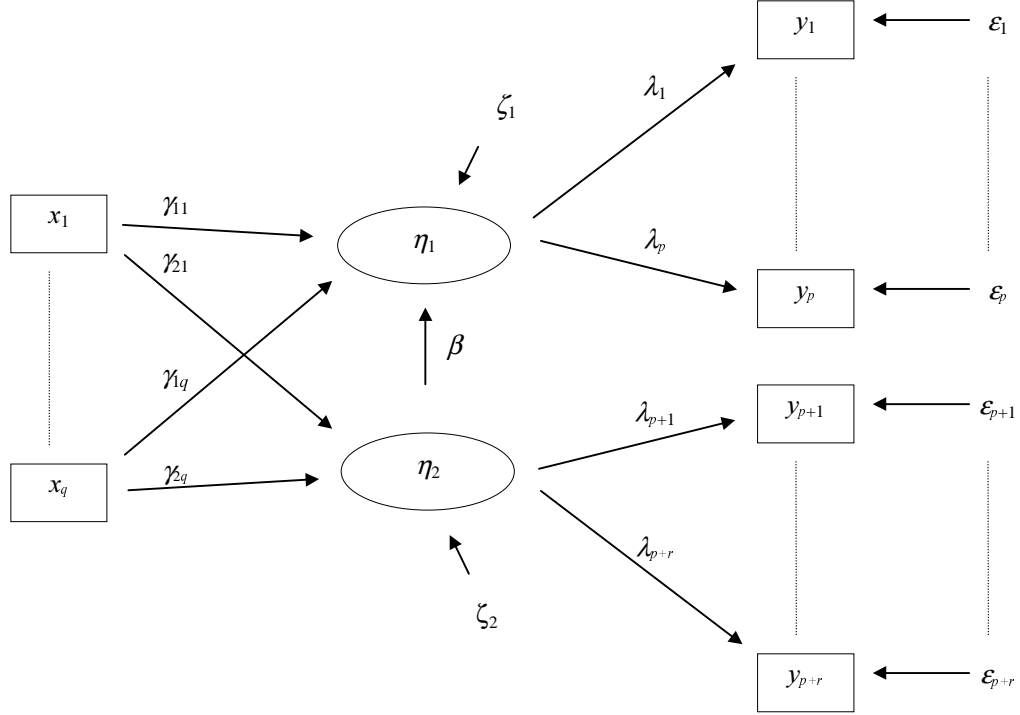
We address these questions empirically by estimating the model after formalizing the specification by labeling the variables and adding random elements. Figure 2 represents the complete formulation for a typical consumer, omitting subscripts indicating individuals for transparency.

The restricted version centers around the latent variable DM-proneness ( $\eta_1$ ), influenced by the observable socio-economic variables  $x_1, \dots, x_q$  with respective coefficients  $\gamma_1, \dots, \gamma_q$ , through a multiple regression specification with disturbance term  $\zeta_1$ , and indirectly observed through the indicators  $y_1, \dots, y_p$ , with respective factor loadings  $\lambda_1, \dots, \lambda_p$  and measurement errors  $\varepsilon_1, \dots, \varepsilon_p$ , assumed independent. Analogous notation and assumptions hold for the latent variable DM-information interest ( $\eta_2$ ) plus its indicators. Equations which relate socio-economic variables to the latent characteristics will be referred to as structural equations. Measurement equations relate the latent constructs to their indicators.

This model is very similar to a MIMIC model (Jöreskog and Goldberger, 1975) where the impact of a number of exogenous variables on a number of endogenous variables is channeled through a single latent variable. We have augmented the original MIMIC model with a second latent characteristic. Such models belong in the class of covariance structure analysis models since the model formulation implies restrictions on the joint covariance matrix of the observable variables. Hence the model can be routinely estimated with the software available for covariance structure analysis models like LISREL, and the evaluation of the model can be based on the statistics that are commonly employed when handling such models. The application is not standard because the indicators are discrete.

**FIGURE 2**

**Path Diagram of a MIMIC model with two Latent Variables**



#### 4. EMPIRICAL STUDY

Omnidata, a DM research and consulting company in the Netherlands, provided the data employed in this section. Over the years nearly all Dutch households have received at least one questionnaire from this firm. The dataset we employ in this study was randomly selected from responders between 1995 and 1997. They number 13288 households. Although the selection performed to generate the dataset we employed was random, the response to the questionnaire may not be random. We first address this issue. If sample selection is performed on an exogenous variable, the effect on the fitted coefficients is relatively innocuous, with no loss of consistency but some loss of efficiency. Selection on an endogenous variable can however introduce bias into the fitted model (Heckman, 1979). Note that the sample

we analyze is not random, but a sample of people who responded to a market research questionnaire. Hence, the observations in our dataset are thus likely to represent consumers who are more DM information interested than the general population due to the fact that the questionnaire results were gathered through the mail. Less DM information interested consumers are also drawn to the questionnaire however, because the letter accompanying the questionnaire promised that direct marketers would use the responses to focus their mailings toward targets wishing to receive information, and spare those indicating no interest. Thus, our sample is likely to include an overrepresentation of the DM information interested and of their opposite members. This might induce some bias away from zero of regression coefficients. We choose to neglect this possible phenomenon since, to the best of our knowledge methods to correct for this kind of selectivity in the LISREL setting are unavailable.

The indicators of DM-proneness are the self-reported incidences of purchase through each of seven large DM outlets in the last year. All are binary, and are referred to throughout as  $y_1$  through  $y_7$ . We use the term outlets here loosely and refer to firms selling through the mail. We recognize our indicators of DM proneness are not perfect, as not all product genres are represented by the seven DM outlets. However, the products most commonly purchased through the mail are available at these DM outlets. The outlets were selected due to their overall appeal and mailing practices. Products available at these outlets are likely to interest most consumers. A few outlets sell books and music, a cosmetics company is represented, and two are major catalogers. The catalogers sell a wide selection of products, ranging from clothes and linens to furniture, sporting goods and electronics. Almost every household – except those on do-not-promote lists – will receive an offer from each of the seven firms each year. The proportion indicating purchase from each outlet is given in the second column of Table 1.

In order to show that DM-proneness is consistent across outlets, we also give in Table 1 the incidence of overlap between purchases from the seven firms. Two figures are calculated for each pair of outlets: (1) the actual percentage indicating purchase at both outlets, and (2) the expected percentage if the actions of purchase at each outlet were independent. Expected percentages are in italics. For every pair the actual overlap far exceeds the expected overlap. Thus, by observing overlap purchase percentages of pairs of outlets, we are led to believe that consumers who purchase at one DM outlet are also more likely to be customers at another DM outlet. This becomes clear also when we inspect the eigenvalues of the correlation matrix, the largest eigenvalue being three times the second largest. This suggests that there is a single common factor driving the purchase incidence variables.



**TABLE 1**  
**Indicators of DM-proneness**

	Percentage overlap with													
	Outlet 1		Outlet 2		Outlet 3		Outlet 4		Outlet 5		Outlet 6		Outlet 7	
	Actual	<i>Expected</i>	Actual	<i>Expected</i>	Actual	<i>Expected</i>	Actual	<i>Expected</i>	Actual	<i>Expected</i>	Actual	<i>Expected</i>	Actual	<i>Expected</i>
Outlet 1	25.1													
Outlet 2	9.8	3.6	14.3											
Outlet 3	5.6	3.2	3.3	1.8	12.6									
Outlet 4	5.7	2.9	3.6	1.7	2.9	1.5	11.6							
Outlet 5	7.8	2.9	5.7	1.6	2.8	1.4	2.9	1.3	11.5					
Outlet 6	3.3	1.7	1.9	1.0	1.8	0.9	1.7	0.8	1.7	0.8	6.8			
Outlet 7	2.1	1.2	1.4	0.7	1.3	0.6	1.3	0.5	0.9	0.5	6.8	0.3	4.8	

**TABLE 2**  
**Observed and expected frequencies of consumers making purchases at n DM outlets**

Outlets with purchase (DMPI)	Frequency	
	Observed	<i>Expected</i>
0	7396	5180.09
1	2621	5333.34
2	1735	2220.33
3	939	488.24
4	423	61.39
5	141	4.41
6	29	0.16
7	4	0.0025

We followed the example of Bawa and Shoemaker (1987) in investigating whether DM purchase indication at the seven firms is consistent. They performed a similar exercise while studying the consistency of coupon-proneness over product classes. We derived an index of DM-proneness (DMPI) by simply summing the indicators of purchase at the seven outlets for each consumer. Values for the DMPI thus range between zero and seven. Table 2 gives a tabulation of the actual number of customers with the eight possible DMPIs. Also given is the expected number of customers, assuming that there is independence between purchase at the firms. We note that there are many more customers with actual DMPI values at the extremes than expected, and that the middle DMPI values are less represented than one would expect. A chi-square test applied to the data in Table 2 shows a significant difference between the expected and observed frequencies ( $\chi^2(7)=20420.84$ ). Again, our hypothesis that DM-proneness is consistent across outlets is confirmed.

We introduce five observed indicators of DM-information interest, binary variables representing desire to receive brochures and catalogs in certain product genres. The genres represent products frequently purchased through the mail. The percentages in the second column of Table 3 give the proportion of our sample indicating desire to receive information by mail in each of the product genres.

Again we raise the issue of consistency, but now across product types. Table 3 shows the overlap percentages of brochure/catalog interest for each pair of product genres. The observed overlap exceeds the expected overlap for each pair of genres. A similar index to the DMPI was then calculated for the information requests. The expected and observed frequencies are given in Table 4. The observed frequencies for the extreme values of the sum of information requests are again overrepresented just as for the DMPI. A chi-square test based on the data in Table 4 yields a significant difference between the expected and observed figures ( $\chi^2(5)=15282.47$ ). Inspection of the eigenvalues of the correlation matrix of the five indicators also suggests that a single common factor is present. We are thus reassured that DM-information interest is consistent across product genres.

Socio-demographic variables  $x_1$  through  $x_5$  represent age, income, household size, education, and the sex of the breadwinner, respectively. These five variables are all categorical and are tabulated in Tables 5 through 9. Both Darian (1987) and Gillett (1976) speculate that upscale households as defined by education and income, working women, and larger households are likely to exhibit shop at home behavior. Darian (1987) makes contradictory hypotheses on the age of likely home shoppers. He expects both young and old to shop at home, young people due to their willingness to take risks, and older people due to the difficulties of travelling to stores. We assume that adventursomeness and curiosity plays a large role in determining if one is interested in DM offers (Cunningham and Cunningham, 1973).

**TABLE 3**  
**Indicators of past purchases through DM**

	Percentage overlap with									
	Clothing		Compact discs and cassettes		Books		Courses		Financial services	
	<i>Actual</i>	<i>Expected</i>	<i>Actual</i>	<i>Expected</i>	<i>Actual</i>	<i>Expected</i>	<i>Actual</i>	<i>Expected</i>	<i>Actual</i>	<i>Expected</i>
Clothing	44.3									
Compact discs and cassettes	20.5	13.0	29.4							
Books	20.6	12.8	18.0	8.5	28.9					
Courses	13.1	8.4	10.5	5.6	10.9	5.5	19.0			
Financial services	7.4	4.7	6.1	3.1	5.9	3.0	4.2	2.0	10.5	

**TABLE 4**  
**Observed and expected frequencies of consumers requesting information for n product genres**

Product genres requested	Frequency	
	Observed	<i>Expected</i>
0	5145	2693.34
1	3123	5307.09
2	2168	3826.41
3	1641	1263.69
4	908	188.69
5	303	9.30

Accordingly, we expect younger, better educated and wealthier consumers to be DM-prone. Our hypothesis regarding female heads of household follows Gillett (1976) who states that working women have less time for shopping and thus are more likely to shop at home. Finally, household size is also hypothesized to have a positive relation with DM-proneness because of the more varied interests present in a larger group of people.

**TABLE 5**  
**Age**

Age ( $x_1$ )	Percent
<36	27.1
36-45	29.3
46-55	18.6
56-65	11.9
>65	13.0

**TABLE 6**  
**Income**

Income ( $x_2$ )	Percent
< Modal	18.8
Modal	51.5
1.5*Modal	17.2
2*Modal	8.0
2.5*Modal	4.5

**TABLE 7**  
**Household size**

Household size ( $x_3$ )	Percent
1 Person	16.5
2 People	42.9
3 People	13.3
4 People	18.9
5 People and up	8.4

**TABLE 8**  
**Education**

Education Level ( $x_4$ )	Percent
No H.S. Diploma	26.0
H.S or Trade school	40.8
Associate's/BA/BS	26.4
Graduate school	6.8

**TABLE 9**  
**Sex of Breadwinner**

Sex of Breadwinner ( $x_5$ )	Percent
Female	15.2
Male, unknown	84.8

***Handling non-normal data***

Our indicators are far from normal and most are binary. Boomsma (1992) suggests in such a case that the weighted least squares (WLS) method is preferred to maximum likelihood (ML), and that using a polychoric correlation matrix is less biased than a matrix of Pearson correlations, see Appendix A. Bollen and Barb (1981) found that the Pearson correlation coefficient of two continuous variables is usually higher than that of the same variables in categorized form. The effect is greatest when the number of categories is relatively small and when the categorized variables are skewed in opposite directions. Jöreskog and Sörbom (1988) compared six measures of correlation for ordinal variables and found that the polychoric correlation is in general the best. Many authors warn that the use of non-normal data will lead to biased estimates of the parameters, standard errors, and  $\chi^2$  tests of model fit (West, Finch, and Curran, 1995). Bollen (1989) states that the use of polychoric correlation matrices in structural equation models yields consistent estimators using ML estimation, but the standard errors, z-tests and chi-square tests are incorrect and suggests WLS estimation is a better choice.

For this study we employ WLS estimation on a polychoric correlation matrix. The choice of this combination of techniques yields consistent estimators of

coefficients and standard errors, based on a correlation matrix closer to the correlation matrix that would be generated from non-categorized data.

## 5. IDENTIFYING THE DM-PRONE AND DM-INFORMATION INTERESTED

We take the socio-demographic variables age, income, education, household size, and sex of breadwinner as the causes of DM-proneness and DM-information interest. The indicators of DM-proneness are the seven indicators of purchase via direct mail in the last year. The five binary variables representing desire to receive catalogs and brochures in five product genres serve as indicators of DM-information interest. Tables 10, 11 and 12 show the estimated coefficients and the corresponding t-values for the structural and measurement equations. The structural equations relate the socio-demographics to DM-proneness and DM-information interest, while the measurement equations equate the DM-proneness and DM-information interest with their indicators.  $R^2$  values are also given.

**TABLE 10**  
**Structural equation parameters**

		DM info interest	Age	Income	Educa- tion	House- hold size	Wo- man	$R^2$
DM- proneness	Parameter	0.26	-0.12	0.056	-0.17	0.23	0.12	0.23
	t-value	(17.40)	(-12.30)	(4.05)	(-13.03)	(15.62)	(5.82)	
DM info interest	Parameter	-	-0.23	0.059	0.004	0.12	0.11	0.11
	t-value		(-24.11)	(4.34)	(0.32)	(8.16)	(5.70)	

**TABLE 11**  
**Measurement equation parameters for DM-proneness**

	DM-proneness		
	Para- meter	t-value	$R^2$
DM outlet #1	1.00		0.68
DM outlet #2	0.94	(55.41)	0.61
DM outlet #3	0.62	(33.27)	0.26
DM outlet #4	0.66	(35.14)	0.29
DM outlet #5	0.94	(54.19)	0.60
DM outlet #6	0.64	(31.29)	0.28
DM outlet #7	0.41	(16.36)	0.11

**TABLE 12**  
**Measurement equation parameters for DM-information interest**

	DM-information interest		
	Para-meter	t-value	R <sup>2</sup>
Books/magazines	1.00		0.70
Music	0.96	(62.94)	0.65
Clothing	0.85	(58.07)	0.51
Courses	0.78	(50.82)	0.43
Financial services	0.63	(34.52)	0.28

Note in Tables 11 and 12 the coefficient value of one for the observed variable Outlet #1 and Books/Magazines, respectively. These values were fixed at one in order to give the latent characteristic a scale, which is a requirement for identification of the model.

The R<sup>2</sup> measures for the seven measurement equations for DM-proneness lie between 0.11 and 0.68. The R<sup>2</sup> values of the DM-information interest indicators range from 0.28 to 0.70. The structural equation that relates the socio-demographics and DM-information interest to DM-proneness has an R<sup>2</sup> of 0.23, as opposed to 0.11 for the equation relating the socio-demographics to DM-information interest.

The chi-square goodness of fit statistic for this model is 1563.13 with 103 degrees of freedom and the fit is inadequate according to that statistic. This is not surprising however, due to the large sample size. The normed fit index was developed as an alternative to the chi-square test because of the chi-square test's sensitivity to sample size. The normed fit index for this model is 0.99, nearly a perfect fit. The goodness of fit index (GFI) for this model is also 0.99 and the parsimony goodness of fit index (PGFI) is 0.67. The GFI attains a value of one when the implied covariance matrix exactly duplicates the observed covariance matrix. The adjustment for parsimony in the PGFI refers to the penalty applied to overly complex models with many parameters (see Bollen, 1990.)

The coefficients of all of the variables in the measurement equations are significant at the  $\alpha=0.05$  level. One coefficient in the structural equations was not significant. Education appears to have no bearing on DM-information interest. Let us scrutinize the coefficients in the structural and measurement equations referring to DM-proneness. The coefficient for age is negative. Thus according to this model, younger people are likelier to be DM-prone. Higher education appears to cause lower levels of DM-proneness, as its coefficient is negative. The coefficients for

income, household size and sex of breadwinner tell us that the typical DM-prone consumer is rather well off, has a larger family size, and is more likely to have a female head of household.

It is interesting to contrast the characteristics of the DM-prone customer with those of the DM-information interested customer. See Table 10. The signs and significance levels of the coefficients in the structural equation tell us what extent socio-demographics are influencing our two latent measures, and if differing portions of the population tend to be DM-prone and be DM-information interested. Our hypothesis that DM-information interest has an effect on DM-proneness is confirmed by its significant, positive coefficient, which is in accordance with our expectations. The socio-demographic qualities of those likely to have increased DM-information interest do not deviate much from those of the DM-prone. They tend to be younger, wealthier, from larger households, and have a female head of household. Note though, that education level appears to influence DM-proneness negatively, while it has no significant effect on DM-information interest. These results contradict both Gillett (1976) who found that in-home shoppers have in general more education, and Darian (1987) who showed that middle income groups are more likely to shop at home. These differences can be attributed to one of two causes: the development of new segments of the population as in-home shoppers since 1987, or the greater breadth of the product categories in this study. Note that all the coefficients in both sets of measurement equations are positive, meaning that the latent characteristic DM-proneness is positively related to all the indicators of purchase by direct mail and that DM-information interest is also positively related to its indicators.

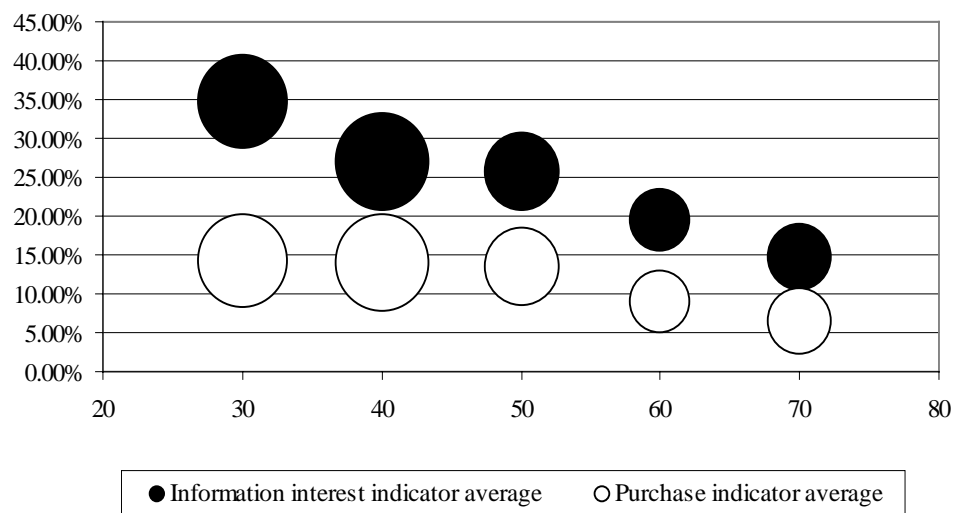
### *Nonlinearity*

Due to the use of polychoric correlations necessitated by the discrete nature of the indicators, it is impossible to discern if the effect of the socio-demographic characteristics would be non-linear. It could be the case that consumers in the middle levels of some socio-demographic characteristics are actually those most (or least) DM-prone. The natural way to deal with this in the case that we have, i.e. categorical explanatory variables with  $k$  possible values, is to code  $k-1$  binary dummies and employ them in the analysis. However, such a solution is not possible in the setting of a polychoric correlation matrix. Polychoric correlations cannot be computed for binary variables for which  $2 \times 2$  tables yields an empty cell. Hence, we employ a slightly informal method to gain some insight directly into the nature of the relationship directly between the indicators and the characteristics, bypassing the latent variables. According to this method, Figures 3, 4, and 5 show that no overly non-monotonic relation exists between age, education and income and the indicators in the measurement equations. Figure 3 displays median age vs. average percent indication for the DM-information interest variables (dark bubbles) and the DM-

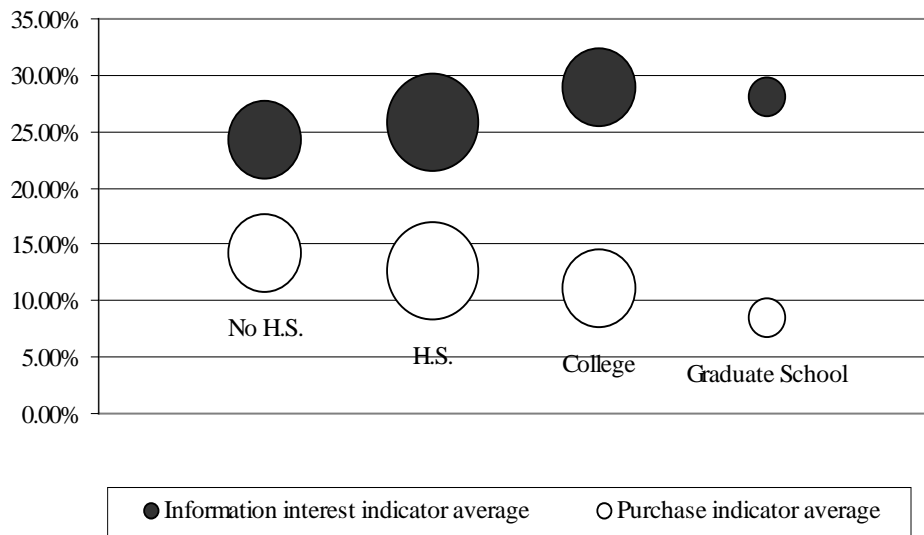


prone indicators (white bubbles). Bubble size relates to the percentage of the population contained in each age group. Figure 3 clearly suggests a monotonic relation between age and the indicators. In Figure 4 we can see a clearly monotonic relation between education and the indicators of DM purchase. Higher levels of education appear to correlate with higher percentages of information interest except for those with a graduate school degree. This group is however very small (6.8%). Figure 5 displays the index of income when compared to the modal income (100=modal, 150=1.5\*modal, etc.). Although the relationship is not monotonic after the 1.5\*modal level, the remaining categories represent less than fifteen percent of the dataset. Summarizing, we take these results as a justification for the assumed linearity.

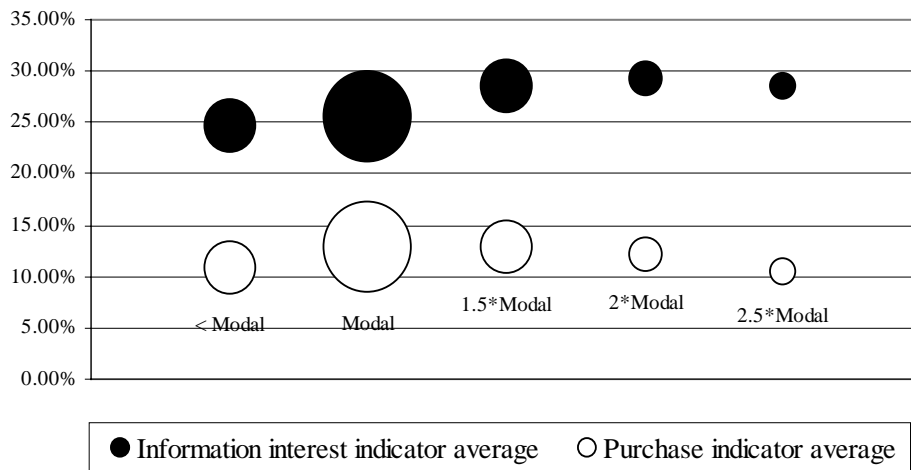
**FIGURE 3**  
**Age category vs. Average percent indication**



**FIGURE 4**  
**Education category vs. Average percent indication**



**FIGURE 5**  
**Income category vs. Average percent indication**



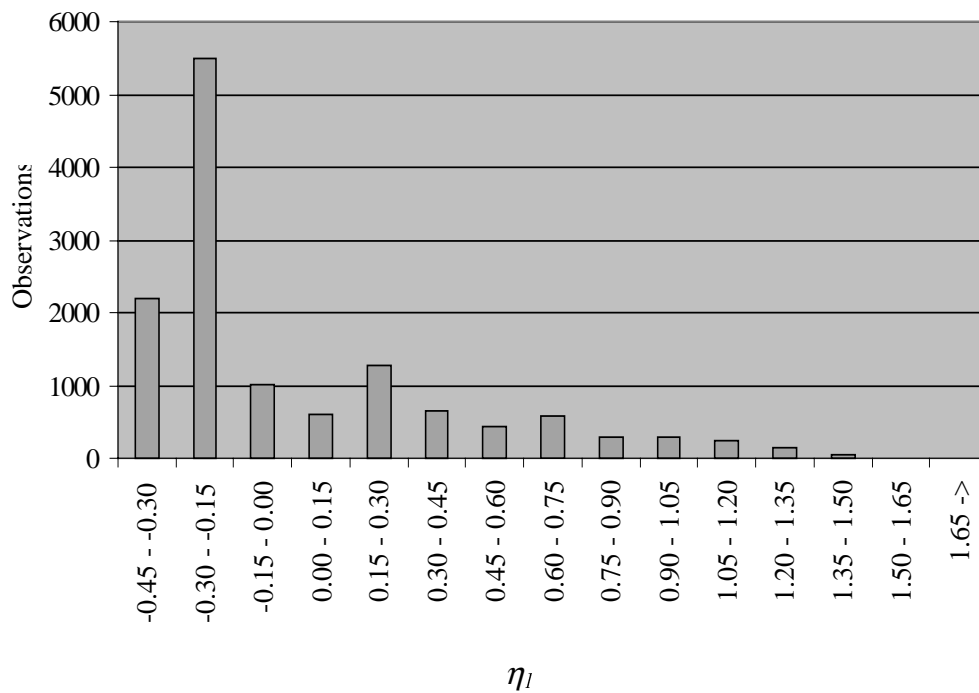
### ***Direction of causality***

Our model appears to confirm that DM-information interest significantly affects one's level of DM-proneness. But what if our hypothesis were just the contrary? Could DM-proneness really be the propensity affecting DM-information interest? Indeed, the two models (one with DM-proneness causing DM-information interest, the other with DM- information interest causing DM- proneness) are equivalent. Bekker, Merckens and Wansbeek (1994) define equivalent models as models for which the data is insufficient to distinguish between their alternative structures. The data and model used in our study cannot be employed to determine which characteristic causes the other. We have hypothesized that interest in direct advertising influences the propensity to make purchases through direct mail because without direct advertising, no purchase can be made.

### ***Distribution of the latent variable***

We now turn our attention to the distribution of the latent variable DM-proneness. Appendix B contains the derivation of the predictor of the latent variable given the observed variables. The distribution is given in Figure 6.

**FIGURE 6**  
**Distribution of DM-proneness**



The distribution of consumers in the continuum of DM-proneness is interesting because it gives the direct marketer a picture what proportion of consumers will be receptive to direct solicitations. A distribution skewed to the right would imply that few people are likely to ever make a purchase through a direct channel. A bimodal distribution would prompt the marketer to work up strategies to better the image of direct mail to the less interested part of the population.

The distribution of DM-proneness is presented in Figure 6. It is skewed heavily to the right. There is a large peak of consumers with low levels of DM-proneness. The distribution also has a long tail extending to the higher values of DM-proneness. Closer examination of the taller mass yields that most of those consumers made no DM purchase in the last year. It appears that there is a large group of non-DM-prone consumers, and a somewhat smaller group of consumers, which is open to DM offers in varying degrees.

## **6. CONCLUSIONS**

The model in the empirical study in this paper shows that both the DM-prone and the DM-information interested tend to be younger, wealthier, have larger households, and have female heads of household. Decreasing education level appears to coincide with higher DM-proneness, but does not influence DM-information interest. The model clearly indicates that DM-information interest has a positive influence on DM-proneness. The characteristics of the DM-information interested and the DM-prone are similar, with the exception of education level. These results differ somewhat from those of earlier studies of in-home shoppers' characteristics. Finally, the distribution of DM-proneness is skewed to the right. There is a considerable portion of the population having little or no intention to buy through the mail.

### ***Managerial Implications***

The models we develop are a first step in furnishing direct marketers with theories on which to found their work. They can help marketers place their customers in the continuum of the DM-prone. Creative people, such as copywriters and offer designers, can use information on the socio-demographics of the DM-prone to better target their customers and prospects.

We do not contend that these models will outperform a standard response model (e.g. logistic regression) in order prediction. Clearly, the ideal way to optimize profits in direct mail is to perform a small test mailing on a random cross-section of the bulk universe, build a predictive model, and cut the bulk universe down to those deemed profitable by the response model. See for example Bult and Wansbeek (1995) and Spring, Leeflang and Wansbeek (1999). However, in the absence of test results, the results in this paper give guidelines for an initial name

selection. For example, direct marketers can seek out lists of addresses for which the socio-demographic profile matches that of the DM-prone. Throckmorton (1992) states that most direct mail offers are never opened. Selecting a group of consumers that are likely to be DM-prone can only increase the chance of a mailing campaign being successful.

Further, direct marketers can employ the results of this study by scanning “media readership tables” for the socio-demographic profile of the DM-prone. Media readership tables rank magazines and newspaper publications by readership in certain socio-demographic categories. Print advertisers looking for their ideal target group often use them to select journals in which to buy pages. A direct marketer seeking a mailing list of DM-prone customers can easily determine which publications have an active subscriber list which is likely to be DM-prone, based on the profile of its readers. Since many magazines and newspapers sell or rent their subscriber lists to third parties for mailings, the results of this study coupled with media readership tables provide an ideal capability to optimally select new mailing lists.

#### ***Limitations and Future Study***

We encountered two methodological difficulties in doing this study. The first arose in the search for a non-linear relation between the causes and the latent constructs in the structural equations. As we decided to employ a polychoric correlation matrix due to its desirable properties, the addition of quadratic or dummy terms was made impossible. Fortunately, this did not have great bearing on our results, but in other studies it may. Research should be done to determine the best solution to this problem. The second difficulty arises from the non-random nature of the selection of our dataset from the general public. Research has been done to study the effects of self-selection in statistical analysis (Heckman, 1979). However, to our knowledge, no related research has been performed in the LISREL setting. This too is a subject lacking in the literature.

DM-proneness was designed to be a market-wide trait as our purpose was to study the characteristics of people interested in all forms of DM advertising. There is a more practical use for product genre-specific and company-specific DM-proneness studies, especially with regard to selection for mailings. Certain socio-demographic segments of the population display greater utility for certain product categories. Studies with the same framework as the one presented here, but specific to a narrow range of products, will most likely yield crucial information about targets for mailings offering products in that narrow range. Likewise, some companies may sell a large number of products in different categories, but with an offer so unique that specific segments of the population are attracted to their offers, almost solely for the

offer's sake. There is room too, therefore, to employ the same framework as in this paper, to model company-specific DM-proneness. Future work in this field calls for estimation of product genre-specific and company-specific models.

A further limitation of this study lies in the lack of candidate socio-demographic variables. We employed only the most basic information: age, education, income, household size, and sex of breadwinner. A browse through the literature yields other socio-demographics that might prove significant in the prediction of DM-proneness, namely presence of children in the household, car ownership, and urbanization of hometown. Future studies may benefit from the incorporation of these variables to determine DM-proneness.

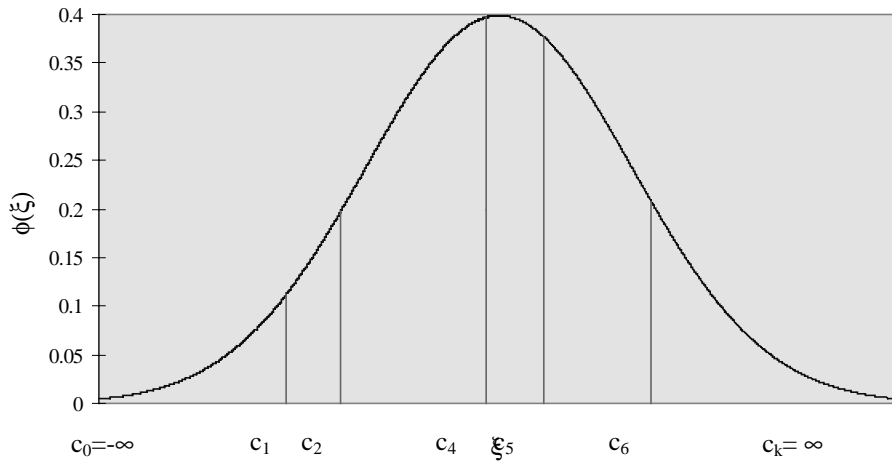
## APPENDIX A

### *Computation of Polychoric correlations and Normal scores*

The polychoric correlation is a measure of association between two ordinal categorical variables, which have two continuous variables underlying them. One assumes the existence of thresholds, which divide up the continuous range of the two variables into categories.

Polychoric correlations and normal scores can be advantageous substitutes for Pearson correlations and integer category identifiers of ordinal variables in structural equation modeling. Problems arise because the category identifiers do not have a metric scale. The procedures for calculating both polychoric correlations and normal score calculations are founded on the assumption that there exists a standard normal variable,  $\xi_i$ , which underlies each ordinal variable,  $x_i$ . The categorization of the ordinal variables is thus assumed to be a function of specific thresholds, between which the standard normal variables take on constant values. One derives the thresholds,  $c_i$ , by comparing the cumulative frequency of values to the cumulative standard normal distribution. See Figure 7.

**FIGURE 7**  
**Illustration of the computation of thresholds**



The normal scores,  $z_i$ , given by (1), are then substituted for the corresponding ordinal category identifiers (Boomsma 1992),

$$z_i = [\phi(c_{i-1}) - \phi(c_i)] / [\Phi(c_i) - \Phi(c_{i-1})], \quad (1)$$

where  $\phi(\bullet)$  and  $\Phi(\bullet)$  are the density and distribution functions of the standard normal distribution.

The correlation between two underlying (standard normal) variates  $\xi_i$  and  $\xi_j$  is called the polychoric correlation coefficient. Polychoric correlations are estimated from two-way tables of pairs of variables. ML estimates of polychoric correlations are computationally intensive. The tetrachoric correlation coefficient is a special case, where the two ordinal observed variables are binary.

## APPENDIX B

### *Derivation of expression for the latent variables in a MIMIC model*

The MIMIC model involves three basic variables:  $\eta$ ,  $y$ , and  $x$ . For completeness we state the form of the model. The structural part of the model is

$$\eta = B\eta + \Gamma x + \zeta$$

and the measurement equations are

$$y = \Lambda_y \eta + \varepsilon.$$

The covariance matrices of  $x$ ,  $\zeta$ , and  $\varepsilon$  are represented by  $\Phi$ ,  $\Psi$ , and  $\Theta_\varepsilon$ , respectively. We assume that all variables are centered. The implied joint covariance matrix of  $\eta$ ,  $y$ , and  $x$  takes on the following form:

$$\Sigma = \begin{bmatrix} \Sigma_{\eta\eta} & \Sigma_{\eta y} & \Sigma_{\eta x} \\ \Sigma_{y\eta} & \Sigma_{yy} & \Sigma_{yx} \\ \Sigma_{x\eta} & \Sigma_{xy} & \Sigma_{xx} \end{bmatrix} = \begin{bmatrix} \Pi\Phi\Pi' + \Psi^* & (\Pi\Phi\Pi' + \Psi^*)\Lambda_y' & \Pi\Phi \\ \Lambda_y(\Pi\Phi\Pi' + \Psi^*) & \Lambda_y(\Pi\Phi\Pi' + \Psi^*)\Lambda_y' + \Theta_\varepsilon & \Lambda_y\Pi\Phi \\ \Phi\Pi' & \Phi\Pi'\Lambda_y' & \Phi \end{bmatrix}$$

where  $\Pi = (\mathbf{I} - B)^{-1}\Gamma$ , and  $\Psi^* = (\mathbf{I} - B)^{-1}\Psi(\mathbf{I} - B')^{-1}$ .

Below we will use

$$\begin{bmatrix} \Lambda_y(\Pi\Phi\Pi' + \Psi^*)\Lambda_y' + \Theta_\varepsilon & \Lambda_y\Pi\Phi \\ \Phi\Pi'\Lambda_y' & \Phi \end{bmatrix}^{-1} = \begin{bmatrix} 0 & 0 \\ 0 & \Phi^{-1} \end{bmatrix} + \begin{bmatrix} -\mathbf{I} \\ \Pi'\Lambda_y' \end{bmatrix} [\Lambda_y\Psi^*\Lambda_y' + \Theta_\varepsilon]^{-1} [-\mathbf{I}, \Lambda_y\Pi]$$

A natural predictor of  $\eta$  given the observables  $x$  and  $y$  is its expectation conditional on  $x$  and  $y$  (see Chen (1981) for the case of fixed  $x$ ):



$$\begin{aligned}
E(\eta|y, \mathbf{x}) &= \left[ (\Pi\Phi\Pi' + \Psi^*)\Lambda'_y, \quad \Pi\Phi \begin{bmatrix} \Lambda_y(\Pi\Phi\Pi' + \Psi^*)\Lambda'_y + \Theta_\varepsilon & \Lambda_y\Pi\Phi \\ \Phi\Pi'\Lambda'_y & \Phi \end{bmatrix}^{-1} \begin{bmatrix} y \\ \mathbf{x} \end{bmatrix} \right] \\
&= \left[ (\Pi\Phi\Pi' + \Psi^*)\Lambda'_y, \quad \Pi\Phi \right] \begin{bmatrix} 0 & 0 \\ 0 & \Phi^{-1} \end{bmatrix} + \begin{bmatrix} -\mathbf{I} \\ \Pi'\Lambda'_y \end{bmatrix} \left[ \Lambda_y\Psi^*\Lambda'_y + \Theta_\varepsilon \right]^{-1} \begin{bmatrix} -\mathbf{I} & \Lambda_y\Pi \end{bmatrix} \begin{bmatrix} y \\ \mathbf{x} \end{bmatrix} \\
&= \Pi\mathbf{x} + \Psi^*\Lambda'_y \left[ \Lambda_y\Psi^*\Lambda'_y + \Theta_\varepsilon \right]^{-1} \left[ y - \Lambda_y\Pi\mathbf{x} \right].
\end{aligned}$$

So the predictor is seen to be a weighted sum of the exogenous variables  $x$  and  $y$  and the residual part  $y - \Lambda_y\Pi\mathbf{x}$  of the indicators. Note that this derivation is general and thus holds for both single and multiple latent variable MIMIC models.

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